Can output explain the predictability and volatility of stock returns?

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Abstract

This paper examines whether a general equilibrium asset pricing model can explain two important empirical regularities of asset returns, extensively documented in the literature: (i) returns can be predicted by a set of macro variables, and (ii) returns are very volatile. We derive a closed-form solution for the equilibrium asset pricing model that relates asset returns to output by using an approximate method proposed by Campbell (Am. Econ. Rev. 83 (1993) 487) and Restoy and Weil (W.P. NBER, No. 6611 (1998)). We obtain evidence on eight OECD economies using both quarterly and annual observations. Equilibrium models seem to fin fewer difficultie in explaining the volatility of returns than their predictability for general output processes. In the case of the US, the observed predictability and volatility of asset returns, for annual frequencies, are broadly compatible with the predictions of equilibrium models for a reasonable specificatio of preferences.

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1. Introduction

The empirical literature on financial markets has provided extensive evidence on two main regularities: (i) (excess) returns are predictable (in the sense that their conditional mean is not a constant) (Fama, 1981, 1990; Cozier and Rahman, 1988; Fama and French, 1988; Balvers et al., 1990; Barro, 1990; Bondt and Bange, 1991; Chen, 1991; Malliriaris and Urrutia, 1991; Bong-Soo, 1992; Marathe and Shawky, 1994; Gallinger, 1994; Hawawini and Keim, 1994; Peiró, 1996; Lee, 1996) and (ii) aggregate stock prices seems to be far more volatile than measures of expected future dividends (LeRoy and Porter, 1981; Shiller, 1981). As it is well known, although both empirical regularities have been often used to challenge the market efficiency paradigm, they do not necessarily contradict agents' rationality to the extent they are risk averse. Thus, Balvers et al. (1990) have shown that equilibrium stock returns in a log-utility representative agent framework will be predictable if output is predictable. Similarly, Grossman and Shiller (1981), have shown that if a economy's representative agent is sufficiently risk averse, equilibrium stock prices could possibly be more volatile than future (constantly) discounted dividends. However, as pointed out by Campbell and Shiller (1988), the predictability and the excess volatility of stock returns are not separate issues. Indeed, excess volatility of asset prices -with respect to the expected sum of future discounted dividends- directly implies some form of forecastability of future returns. An interesting issue is, then, whether fundamentals can simultaneously explain, in equilibrium, the observed volatility and forecastability of asset returns.

Despite its relevance, there have been so far very few attempts to study this question. One exception is Kandel and Stambaugh (1991), who calibrate numerically the implications of an intertemporal asset pricing model with generalized isoelastic preferences (Epstein and Zin, 1989; Weil, 1989) on the autocorrelation and volatility of asset returns when consumption follows a simple univariate Markov process. One obstacle to address this issue in a more general setting, is the difficulty in obtaining closed-form solutions of equilibrium asset pricing models that could permit returns to be expressed explicitly in terms of economic variables when agents are risk-averse.

In this paper we use a simple framework to study the ability of equilibrium asset pricing models to explain the predictability and volatility of returns for a general specification of preferences and of the output process. The analysis makes use of the "approximation technology" developed in Campbell (1993) and Restoy and Weil (1998) to obtain approximate closed-form solutions that relate asset returns to output. The implications of the model are tested using data on eight industrialized countries.

The organization of the paper is as follows. In Section 2 we study whether macroeconomic variables can be used to predict stock returns in a sample of eight OECD economies and compare the volatility of returns with that of the variables usually considered as fundamentals of asset prices. Section 3 describes the model and its implications for the predictability and volatility of returns. Section 4 tests the implications of the model for all eight countries following a multivariate approach. Finally, Section 5 contains some concluding remarks.

2. Stylized facts

In this section we provide evidence on the predictability and volatility of stock returns for the US, the UK, Canada, France, Germany, Italy, Japan and Spain. We use quarterly and annual data on returns, dividend yields, output (industrial production) and three-month interest rates from 1970 to 1996.

2.1. Predictability of returns

We study the predictable time variation in stock returns by regressing real stock returns on the explanatory variables usually employed in the literature to document the predictability of returns. These variables are the one-period lagged stock return (r_t), the lagged dividend yield[1] (dy_t), the lagged growth rate of aggregate output[2] (y_t) and short-term interest rates (re_t). The latter variable is detrended by subtracting one-year moving average.[3]

The stock market indexes and the gross dividend yields were obtained from Morgan Stanley Capital International (MSCI). Short-term interest rates, output and CPI inf ation are taken from the OECD data base. The latter is used to convert nominal returns into real ones.

Table 1 presents the results of the regressions. For each regression the table reports the estimated coeff cients, the adjusted coeff cient of determination, and the signif - cance level for a Wald test of the hypothesis that all coeff cients are zero. Heteroskedasticity-consistent covariance matrices are used.

With quarterly data, there is some (weak) evidence of stock returns' predictability only in the cases of Italy, United Kingdom, and United States.[4] The forecasting power of each of the right hand side variables generally varies from country to country. In all cases, however, the model explains only a very limited part of the variability of returns.

When we use annual observations, the forecasting variables are jointly signif cant at reasonable levels of signif cance only for the US and the UK. In those two cases the forecasting power of the right hand side variables is, however, remarkable. The estimated model explains 16% of the variability of returns for the US and 27% for the UK. Thus, the forecastability of stock returns seems to increase with the time interval over which returns are measured. This result is consistent with those of Campbell and Shiller (1988) and Fama and French (1988). The sign pattern for dividend yields and interest rates is stable across time measurement intervals,

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[1] Price-earnings ratios have been found to predict returns in the US (Campbell and Shiller, 1988; Fama and French, 1988).

[2] This variable is used to forecast stock returns in Marathe and Shawky (1994), Balvers et al. (1990) and Chen (1991).

[3] This variable is also used to forecast stock returns in Campbell (1990).

[4] The US results reported for both frequencies use the S&P500 index, and the dividend yield of this index (Citibase) from 1947 to 1996.

Table 1

Predicting returns. The sample period is 1970–1996 except for United States annual data (1947–1996). r_{t+1} is the real stock return (MSCI, OECD). The forecasting variables are the lagged stock return (r_t), the lagged growth rate of aggregate output (y_t) (OECD), the lagged gross dividend yield (dy_t) (MSCI) and the short-term interest rate (re_t) (OECD). The reported R^2 is the adjusted coeff cient of determination. F is the p-value of the F-test for all coeff cients in the regression to be zero, except for the constant. Standard errors are heteroskedastic-consistent (Robust–White). Signif cance at the 5% level is denoted by $*$ and at the 15% level by $**$.

$$r_{t+1} = \alpha_0 + \alpha_1 r_t + \alpha_2 y_t + \alpha_3 re_t + \alpha_4 dy_t + v_{t+1}$$

Country	α_0	α_1	α_2	α_3	α_4	R^2	F
Quarterly data:							
1. United States	−0.018	0.090	−0.161	−0.016*	0.007**	0.053	0.006
2. United Kingdom	−0.086	0.169	−0.816	−0.006	0.020	0.084	0.012
3. Canada	−0.035	0.231*	0.242	−0.003	0.012	0.021	0.192
4. France	−0.016	0.016	−0.367	−0.016*	0.006	0.011	0.281
5. Germany	−0.022	0.032	−0.122	−0.013*	0.008	0.002	0.391
6. Italy	−0.052	0.121	−0.824*	−0.006	0.021	0.050	0.058
7. Japan	−0.008	−0.029	−0.079	−0.025*	0.014	0.027	0.146
8. Spain	−0.025	0.025	0.709**	−0.007	0.004**	0.0010	0.294
Annual data:							
1. United States	−0.070	0.146	0.967*	−0.019	0.034**	0.164	0.018
2. United Kingdom	−0.585**	0.184	1.297	−0.032**	0.121*	0.271	0.029
3. Canada	−0.041	0.153	−0.279	−0.014	0.025	−0.117	0.846
4. France	0.032	−0.187	−1.393**	−0.019	0.011	−0.012	0.470
5. Germany	−0.049	−0.158	−0.662	−0.031*	0.029	0.049	0.294
6. Italy	−0.314	0.331	−1.070**	−0.002	0.123	−0.021	0.494
7. Japan	−0.038	0.115	−1.131	−0.011	0.076**	0.019	0.372
8. Spain	−0.044	0.390**	−0.982	0.001	0.013	0.037	0.324

although there are some shifts in the magnitude and statistical significance of the coefficients.

Therefore, we have found some empirical evidence on the ability of the dividend yield, the growth rate of output, the short-term interest rate and the lagged returns, to forecast stock returns. This forecasting ability is particularly high in the case of the UK and the US and for annual frequencies.

2.2. *Excessive volatility in stock returns*

Variances of the different variables considered are reported in Table 2. This table shows that returns are much more volatile—in all countries—than any of the variables normally used to estimate the stock market fundamentals: interest rates, the dividend yield or output growth. The highest volatility of stock returns is found in Italy, Spain and the UK.

In the following sections we assess the ability of equilibrium asset pricing models to explain both stylized facts illustrated in this section; namely the predictability and (excess) volatility of stock returns.

Table 2
Variances[a]

Country	var(r_t)	var(y_t)	var(dy_t)	var(re_t)
Annual data:				
1. United States	2.836	0.322	0.013	0.026
2. United Kingdom	7.311	0.178	0.025	0.086
3. Canada	2.597	0.337	0.006	0.053
4. France	6.181	0.157	0.028	0.067
5. Germany	5.411	0.218	0.012	0.055
6. Italy	8.793	0.513	0.006	0.110
7. Japan	6.610	0.381	0.012	0.045
8. Spain	7.150	0.278	0.158	0.133
Quarterly data:				
1. United States	0.528	0.053	0.013	0.007
2. United Kingdom	1.150	0.039	0.016	0.017
3. Canada	0.658	0.041	0.006	0.015
4. France	1.254	0.029	0.028	0.016
5. Germany	0.897	0.072	0.011	0.013
6. Italy	1.774	0.164	0.006	0.018
7. Japan	1.154	0.045	0.014	0.009
8. Spain	1.456	0.079	0.133	0.032

[a] See Table 1 for description of variables. Variances are multiplied by 100.

3. The model

3.1. The economy

This section presents a general equilibrium discrete-time model relating asset prices to real macroeconomic variables. The economy is similar, except for the agent's preferences, to Lucas (1978) and Mehra and Prescott (1985). Preferences are of a generalized isoelastic form (GIP) as proposed by Epstein and Zin (1989) and Weil (1989).

Take one perishable consumption good, a fruit, which is produced by non-reproducible identical trees whose number is normalized, without loss of generality, to be equal to the size of the constant population. Let Y_t denote the number of fruits falling from a tree at time t. Y_{t+1} then follows the process

$$Y_{t+1} = Y_t e^{\psi_{t+1}}, \tag{1}$$

where the growth rate of output ψ_{t+1}, is a Markovian random variable.

The economy is inhabited by many identical infinitely-lived consumers. Let P_t, N_t and C_t denote, respectively, the fruit price, the number of trees (shares) and consumption of a representative agent (at period t). The one-period budget constraint faced by the representative consumer is

$$C_t + P_t N_{t+1} = (P_t + Y_t)N_t \qquad t \geq 0, \tag{2}$$

with $N_0 > 0$. Let $R_{t+1} = \dfrac{P_{t+1} + Y_{t+1}}{P_t}$ be the one-period real rate of return on the tree (the wealth portfolio), and $W_t = (P_t + Y_t)N_t$ the wealth that the agent possesses at time t. The budget constraint (2) can be rewritten as

$$W_{t+1} = R_{t+1}(W_t - C_t). \tag{3}$$

The identical consumers have generalized isoelastic preferences with constant elasticity of intertemporal substitution $\left(\dfrac{1}{\rho}\right)$ and constant coefficient of relative risk aversion (γ).[5]

Epstein and Zin (1989) have shown that for any asset j with gross rate of return $R_{j,t+1}$ between dates t and t+1 the following Euler equation must be satisfied:

$$E_t\left[\beta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R_{t+1}^{\theta-1} R_{j,t+1}\right] = 1, \tag{4}$$

[5] The advantage of this specification for the preferences lies in its ability to generalize, in a non-expected utility framework, the commonly used time-additive isoelastic expected utility specification. Thus, Epstein–Zin (1989) utility allows for an independent parametrization of attitudes toward risk and attitudes toward intertemporal substitution.

where θ is equal to $\frac{1-\gamma}{1-\rho}$, the operator E_t denotes mathematical expectation conditional on information available at t, and β is the time-preference parameter.

Naturally, equilibrium in this endowment economy implies $C_t = Y_t$. To make the link between output and the rate of return on wealth explicit, one must go beyond the Euler equation and use the information provided by the budget constraint. This objective requires that we circumvent the difficulty that budget constraints are multiplicative in consumption (output) and the rate of return on wealth.

3.2. Linear approximation to the equilibrium solution

Campbell (1993) and Restoy and Weil (1998) have derived a method of obtaining approximate closed-form solutions to the problem above. That solution is useful to us as it allows the predictability and volatility of asset returns to be related to those of their underlying (real) fundamentals.

Following Restoy and Weil (1998) the non-linear budget constraint can be approximated by this log-linear expression

$$r_{t+1} \approx y_{t+1} - a_{t+1} + \frac{1}{\delta} a_t - k, \tag{5}$$

where y_{t+1} denotes the growth rate of aggregate output, a_t is the log of the consumption wealth ratio and k and δ $(0<\delta<1)$ are two linearization constants.

In the case where output growth is conditionally homoskedastic, Restoy and Weil (1998) demonstrate that the rate of return of the market portfolio in equilibrium can be approximately written as

$$r_{t+1} = \mu + \rho y_{t+1} + (1-\rho) S_{t+1} \sum_{j=0}^{\infty} \delta^j y_{t+j+1}, \tag{6}$$

where S_{t+1} is the innovation operator (i.e. $S_{t+1} x_{t+1} = E_{t+1} x_{t+1} - E_t x_{t+1}$).

Expression (6) makes it clear that both the first and second-order moments of aggregate returns depend mainly on the elasticity of intertemporal substitution. The coefficient of relative risk aversion does not directly appear in the expression above although it is embedded in the discount factor, δ.

As shown by Weil (1989) the equity premium in this model depends mainly on the coefficient of relative risk aversion. Therefore, we can be sure that choosing ρ to match the predictability and volatility of returns does not affect the extent to which the model is able to solve the equity premium puzzle.[6]

[6] Kandel and Stambaugh (1991) obtained that a coefficient of relative risk aversion of around 29 suffices to match the observed equity premium. Since Mehra and Presscot (1985), it has been normally considered that such a risk aversion was too high to be realistic. However, Weil (1992), making use of the results by Kimball (1990), suggests that such a high coefficient is consistent with moderately risk-averse agents when markets are incomplete.

3.3. Predictability of returns and output

Eq. (6) specifies that the log stock return in period $t+1$ is a weighted combination (with weights ρ and $(1-\rho)$) of the current growth rate of aggregate output in that period and changes in the expected growth rate of output produced between t and $t+1$. Furthermore, the parameter that governs the output–returns (or consumption–returns) relationship is the elasticity of intertemporal substitution. The coefficient of relative risk aversion (γ) affects only the constant term (μ) in Eq. (6) and the discount term (δ).

Taking conditional expectations of both sides in (6) we find that:[7]

$$E_t(r_{t+1}) = \mu + \rho E_t(y_{t+1}). \tag{7}$$

Therefore, the model implies that returns will be predictable to the extent the output is predictable, and by the same variables that help to predict output, if any.

In our output–returns relationship, two special cases are worth noting:

- If $\rho=1$, Eqs. (6) and (7) become

  $$r_{t+1} = -\ln\beta + y_{t+1}, \tag{8}$$

  $$E_t(r_{t+1}) = m + E_t(y_{t+1}). \tag{9}$$

  Those expressions are equivalent to those obtained by Balvers et al. (1990) using logarithmic expected-utility preferences.
- If $\rho \neq 1$, the right hand side of Eq. (6) takes different expressions according to the process followed by the growth rate of aggregate output. For example, we can derive returns when output growth follows a general stationary ARIMA process (see Appendix A) by making use of its MA representation. Then, if y_{t+1} follows an AR(1) process

  $$y_{t+1} = \phi y_t + \varepsilon^y_{t+1}, \tag{10}$$

  Eq. (6) becomes

  $$r_{t+1} = \mu + \rho y_{t+1} + \frac{(1-\rho)}{(1-\delta\phi)}\varepsilon^y_{t+1}, \tag{11}$$

  and

  $$E_t(r_{t+1}) = \mu + \phi\rho y_t. \tag{12}$$

  Then, if output follows an AR(1) process, it is legitimate to use one-period lagged output to predict returns. This is the approach taken in Marathe and Shawky (1994).

[7] Since the conditional expectations operator satisfies $E_jE_k=E_{\min(j,k)}$ it follows that for $m\geq 1$,

$$E_{t+1-m}S_{t+1}y_{t+1+k} = E_{t+1-m}(E_{t+1}y_{t+1+k}-E_t y_{t+1+k}) = E_{t+1-m}y_{t+1+k}-E_{t+1-m}y_{t+1+k} = 0.$$

Therefore, the proposed approach permits the predictability of stock returns to be related to predictability of output for a general specification of preferences and of the process followed by output.

3.4. General volatility bound

Subtracting (7) from (6) the model implies that innovations in returns are related to innovations in output by the expression:

$$S_{t+1}r_{t+1} = S_{t+1}y_{t+1} + (1-\rho)S_{t+1}\sum_{j=1}^{\infty}\delta^j y_{t+j+1}. \tag{13}$$

Therefore, the volatility of stock returns should be completely explained by the volatility of realized and expected output. In principle, that relationship depends on the conditional distribution of output. However, we can find an upper bound for the variance of $S_{t+1}r_{t+1}$ for a given variance of y_{t+1}.

We can write y_{t+1} as its unconditional expectation plus the sum of its past innovations:[8]

$$y_{t+1} = E(y) + \sum_{j=0}^{\infty} S_{t+1-j}y_{t+1}. \tag{14}$$

Since y_{t+1} is stationary, it holds that $\mathrm{var}(S_{t+1-j}y_{t+1}) = \mathrm{var}(S_{t+1}y_{t+1+j}) = \sigma_j^2$ independent of t.[9] Therefore, since innovations are serially uncorrelated, we know from (14) that the variance of the sum is the sum of variances:

$$\mathrm{var}(y_{t+1}) = \sum_{j=0}^{\infty}\mathrm{var}(S_{t+1-j}y_{t+1}) = \sum_{j=0}^{\infty}\sigma_j^2. \tag{15}$$

In expression (13) all innovations are realized at the same moment in time. So, we cannot state that the variance of the sum is the sum of the variances since contemporaneous innovations may be correlated. In fact, for a given $\sigma_0^2, \sigma_1^2 \ldots$, the maximum variance of the summation term in (14) occurs when the elements in the sum are perfectly positively correlated. This means then that $S_{t+1}y_{t+1+j} = \dfrac{\sigma_j}{\sigma_0}S_{t+1}y_{t+1}$. Substituting this into (14) implies $\hat{y}_{t+1} = \sum_{j=0}^{\infty}\dfrac{\sigma_j}{\sigma_0}\varepsilon_{t+1-j}$ where hat denotes a variable

[8] If we regard $E(y)$ as $E_{-\infty}$, then this expression is simply a tautology. It tells us, though, that y_{t+1} are just different linear combinations of the same innovations in output that enter into the linear combination in (13) that determine $S_{t+1}r_{t+1}$. We can thus ask how large $\mathrm{var}(S_{t+1}r_{t+1})$ should be for a given $\mathrm{var}(y_{t+1})$.

[9] We introduce the assumption that y_t is jointly stationary with information, which means that the unconditional covariance between y_t and z_{t-k}, where z_t is any information variable (which might be y_t itself), depends only on k, and not on t. It follows that we can write expressions like $\mathrm{var}(S_{t+1}y_{t+1+j})$ without a time subscript. (For a more complete explanation see Shiller (1991).)

minus its mean $\hat{y}_{t+1} = y_{t+1} - E(y)$ and $e_{t+1} = S_{t+1} y_{t+1}$. Thus, if $\text{var}(S_{t+1} r_{t+1})$ is to be maximized for a given $\sigma_0^2, \sigma_1^2, \ldots$, the output process must be a moving average process in terms of its own innovations.

We can now find the maximum possible variance for $S_{t+1} r_{t+1}$ for a given variance of y_{t+1}. Since the innovations in (13) are perfectly positively correlated it holds that

$$\text{var}(S_{t+1} r_{t+1}) = \left(\sigma_0 + \sum_{j=1}^{\infty} \delta^j (1-\rho) \sigma_j\right)^2. \tag{16}$$

If we maximize this expression subject to the constraint $\text{var}(y_{t+1}) = \sum_{j=0}^{\infty} \sigma_j^2$ with respect to $\sigma_0, \sigma_1, \ldots$, we obtain the maximum variance of returns by using the expression

$$\text{var}(S_{t+1} r_{t+1}) = \left(1 + (1-\rho)^2 \frac{\delta^2}{1-\delta^2}\right) \text{var}(y_{t+1}), \tag{17}$$

which constitutes an upper volatility bound of stock returns. Therefore, for any stationary output process it holds that

$$\text{var}(S_{t+1} r_{t+1}) \leq \left(1 + (1-\rho)^2 \frac{\delta^2}{1-\delta^2}\right) \text{var}(y_{t+1}). \tag{18}$$

This implication of the model will be empirically explored in Section 4.

4. Empirical analysis

Before addressing the empirical exercise it is important to notice the problems in linking theory to data. The model describes an economy with the following characteristics: no trade, complete markets, no corporate sector, no technological change, no investment in capital, no money and no government sector. The data come from a world with open economies, incomplete markets, corporate sectors, important technological change, investments in capital, money and government sectors. Therefore, we should not attempt to explain all features of the data with such a stylized model. We will rather focus on the extent to which two important stylized facts (predictability, volatility) are compatible with standard equilibrium asset pricing models.

In order to test the ability of the model to explain the predictability and volatility of asset returns we proceed as follows. We first study if the evidence on predictability of asset returns is consistent with Eq. (7). Second, we check if the volatility of asset returns is consistent with that predicted by the model and the volatility bound obtained in Section 3. We then test if the model is able to match both the predictability and volatility of asset returns for an economically meaningful specification of preferences. Before we proceed to address those issues directly we need to specify an empirical model that allows the estimation of the conditional mean and variance of the relevant variables. Rather than rely on a specific theoretical model, we assume that expectations are generated by a vector autoregression (VAR).

4.1. A model for output and returns

We will define a vector z with four elements, the first of which is the real stock return. The second element in the vector is the growth rate of output. The remaining elements are the dividend yield and the (detrended) short-term interest rate. We then assume that the vector z_{t+1} follows a first-order VAR:[10]

$$z_{t+1} = \alpha + Az_t + w_{t+1}.$$

Next, we define a four-element vector $i1$, whose first element is 1 and whose other elements are all 0. This vector picks out the real stock return r_{t+1} from the vector z_{t+1}:$r_{t+1} = i1'z_{t+1}$ and $S_{t+1}r_{t+1} = i1'w_{t+1}$. We also define a second vector $i2$ whose second element is 1 and the rest are all 0 to obtain $S_{t+1}y_{t+1} = i2'w_{t+1}$. As the first-order VAR generates a simple multi-period forecast of future growth rates of aggregate output, we can obtain:

$$S_{t+1}\sum_{j=0}^{\infty}\delta^j y_{t+1+j} = i2'\sum_{j=0}^{\infty}\delta^j A^j w_{t+1} = i2'(I-\delta A)^{-1}w_{t+1}. \tag{19}$$

Since for annual frequencies we have a small number of observations for countries other than the US, we have jointly estimated only the equations corresponding to output and returns in those cases. Equations corresponding to dividend yields and short-term interest rates have been individually estimated. In the rest of the cases (all quarterly estimations and the annual estimation for the US) the whole four-equation VAR has been estimated jointly.

Tables 3 and 4 report the matrix of estimated first-order VAR coefficients and the values of ρ for quarterly and annual data. Standard errors are computed from a heteroskedastic-consistent matrix. Significance at the 5% level is denoted by $*$ and at 15% level by $**$. The last two columns of the table report the adjusted coefficient of determination R^2 and the joint significance level of the VAR forecasting variables.

Notice that Eq. (6) can be seen as a restricted version of the first equation of the VAR model. All five coefficients in this equation will be determined by the structural parameters μ and ρ and the VAR coefficients in the rest of the equations. Similarly, the estimated parameters of the restricted VAR model together with Eq. (19) permit an estimate of the volatility of (model-consistent) returns to be obtained.

[10] The assumption that the VAR is first-order is not restrictive, since a higher-order VAR can always be expressed as a first-order form in the manner discussed by Campbell and Shiller (1989). However, when we use the values of the Schwarz (1978) criteria for the choice of the lag length in the VAR, the minimized value of the criterion is always associated with the first-order system in the quarterly cases. In the annual case there are not sufficient degrees of freedom for the estimation of a higher-order VAR.

Table 3
First Order Vector Autoregression Model-Quarterly data. This table reports coeff cient estimates for a quarterly 1-lag VAR that includes r_t, y_t, re_t and dy_t. The sample period is 1970:1 to 1996:4 except for the US in which is 1947:1 1996:4. The reported R^2 is the adjusted coeff cient of determination. F is the p-value of the F-test for coeff cients in the regression to be zero, except for the constant. ρ is the GMM estimate obtained from the restricted VAR model. χ^2_3 is the p-value of the χ^2 statistic for the three overidentifying restriction of the model. Standard errors are heteroskedastic-consistent (Robust–White). Signif - cance at the 5% level is denoted by $*$ and at the 15% level by $**$

Country		r_t	y_t	re_t	dy_t	R^2	F
United States	r_{t+1}	0.090	−0.161	−0.016*	0.007**	0.053	0.006
	y_{t+1}	0.093*	0.363*	−0.002	−0.001	0.229	0.000
	re_{t+1}	0.819	7.845*	0.350*	−0.042	0.206	0.000
	dy_{t+1}	−0.125	1.597	0.072*	0.967*	0.925	0.000
	ρ	0.577	χ^2_3=13.29 (0.004)				
United Kingdom	r_{t+1}	0.169	−0.916	−0.006	0.020	0.084	0.012
	y_{t+1}	−0.004	−0.048	0.001	−0.005*	0.073	0.020
	re_{t+1}	−2.117*	2.154	0.622*	−0.135**	0.439	0.000
	dy_{t+1}	−1.172**	6.555	0.035	0.829*	0.701	0.000
	ρ	−6.888	χ^2_3=1.408 (0.703)				
Canada	r_{t+1}	0.231*	0.242	−0.003	0.012	0.021	0.192
	y_{t+1}	0.043*	0.434*	−0.004*	−0.003	0.320	0.000
	re_{t+1}	0.653	13.921*	0.546*	−0.051	0.363	0.000
	dy_{t+1}	−0.544	−0.798	0.036	0.889*	0.817	0.000
	ρ	1.103	χ^2_3=3.925 (0.269)				
France	r_{t+1}	0.016	−0.367	−0.016*	0.006	0.011	0.281
	y_{t+1}	0.017	0.090	−0.001	−0.001	0.008	0.310
	re_{t+1}	0.214	11.855*	0.629*	−0.059	0.422	0.000
	dy_{t+1}	0.088	−0.544	0.102*	0.931*	0.875	0.000
	ρ	15.730	χ^2_3=2.429 (0.488)				
Germany	r_{t+1}	0.032	−0.122	−0.013*	0.008	0.002	0.390
	y_{t+1}	0.038**	−0.247**	0.002	−0.004**	0.055	0.046
	re_{t+1}	−0.141	5.195*	0.733*	−0.054	0.558	0.000
	dy_{t+1}	0.072	0.124	0.080*	0.938*	0.875	0.000
	ρ	−1.194	χ^2_3=4.780 (0.188)				
Italy	r_{t+1}	0.121	−0.824*	−0.006	0.021	0.050	0.058
	y_{t+1}	0.055*	−0.313*	−0.003**	0.001	0.097	0.007
	re_{t+1}	−1.442**	10.100*	0.571*	−0.173	0.421	0.000
	dy_{t+1}	−0.077	1.012	0.035	0.827*	0.669	0.000
	ρ	2.452*	χ^2_3=1.274 (0.735)				
Japan	r_{t+1}	−0.029	−0.079	−0.025*	0.014**	0.027	0.146
	y_{t+1}	0.034**	0.267*	−0.004*	0.000	0.151	0.000
	re_{t+1}	−0.128	9.113*	0.823*	−0.014	0.673	0.000
	dy_{t+1}	0.033	−0.444	0.038**	0.921*	0.961	0.000
	ρ	2.496	χ^2_3=3.731 (0.291)				
Spain	r_{t+1}	0.025	0.709*	−0.007	0.004**	0.010	0.294
	y_{t+1}	0.014	−0.184**	−0.002	−0.001*	0.044	0.073
	re_{t+1}	−1.548	7.234	0.426*	−0.011	0.196	0.000
	dy_{t+1}	−0.674	−3.610	0.090**	0.961*	0.938	0.000
	ρ	5.993	χ^2_3=13.29 (0.004)				

Table 4
First order vector autoregression model-annual data. This table reports coefficient estimates for an annual 1-lag VAR that includes r_t, y_t, re_t and dy_t. The sample period is 1970 to 1996 except for United States (1947–1996). The reported R^2 is the adjusted coefficient of determination. F is the p-value of the F-test for coefficients in the regression to be zero, except for the constant. ρ is the GMM estimate of ρ obtained from the restricted VAR model. χ^2_3 is the p-value of the χ^2 statistic for the three overidentifying restriction of the model. Standard errors are heteroskedastic-consistent (Robust–White). Significance at the 5% level is denoted by ∗and at the 15% level by ∗∗

Country		r_t	y_t	re_t	dy_t	R^2	F
United States	r_{t+1}	0.146	−0.967∗	−0.019	0.034∗∗	0.164	0.018
	y_{t+1}	0.143∗	−0.268∗∗	−0.005	0.002	0.156	0.022
	re_{t+1}	0.936	5.716	0.082	0.007	−0.002	0.433
	dy_{t+1}	0.438	2.499	0.099	0.862∗	0.748	0.000
	ρ	2.419∗	χ^2_3=4.99 (0.171)				
United Kingdom	r_{t+1}	0.184	1.297	−0.031∗∗	0.120∗	0.271	0.029
	y_{t+1}	0.056∗∗	0.056	−0.006∗	−0.004	0.373	0.007
	re_{t+1}	1.992	−2.409	0.008	−0.161	−0.118	0.850
	dy_{t+1}	−0.773	−5.974	0.223∗∗	0.076	0.095	0.196
	ρ	7.715	χ^2_3=2.13 (0.54)				
Canada	r_{t+1}	0.153	−0.279	−0.014	0.025	−0.117	0.846
	y_{t+1}	0.107∗∗	0.146	−0.017∗	0.008	0.332	0.012
	re_{t+1}	6.204∗∗	11.641∗∗	0.026	1.118∗∗	0.165	0.098
	dy_{t+1}	0.327	1.856	0.075	0.844∗	0.559	0.000
	ρ	0.342	χ^2_3=0.985 (0.804)				
France	r_{t+1}	−0.187	−1.393∗∗	−0.019	0.011	−0.012	0.470
	y_{t+1}	−0.023	0.056	−0.011∗	0.001	0.414	0.003
	re_{t+1}	3.360∗∗	34.973∗	−0.269∗∗	0.291	0.379	0.006
	dy_{t+1}	0.835	6.349	0.148∗∗	0.809∗	0.556	0.0002
	ρ	3.365∗∗	χ^2_3=3.360 (0.339)				
Germany	r_{t+1}	−0.158	−0.662	−0.031∗	0.029	0.049	0.294
	y_{t+1}	0.053	0.171	−0.012∗	0.001	0.399	0.004
	re_{t+1}	2.945	27.007∗	−0.102	0.549	0.118	0.159
	dy_{t+1}	0.676	6.793∗	0.121∗	0.819∗	0.609	0.001
	ρ	1.465	χ^2_3=6.852 (0.076)				
Italy	r_{t+1}	0.331	−1.071∗∗	−0.002	0.123	−0.020	0.494
	y_{t+1}	−0.097	0.140	−0.014∗	0.004	0.376	0.008
	re_{t+1}	2.183	6.110	−0.202	0.830	−0.036	0.546
	dy_{t+1}	−1.374∗	0.120	0.027	0.060	0.230	0.053
	ρ	1.399	χ^2_3=4.338 (0.227)				
Japan	r_{t+1}	0.115	−1.131	−0.011	0.076∗∗	0.019	0.372
	y_{t+1}	0.150∗	−0.175	−0.005	0.011	0.377	0.006
	re_{t+1}	1.851	21.217	0.126	−0.041	0.434	0.002
	dy_{t+1}	−0.008	2.139∗∗	0.026	0.680∗	0.761	0.000
	ρ	1.811∗∗	χ^2_3=3.890 (0.273)				
Spain	r_{t+1}	−0.391∗∗	−0.982	0.001	0.136	0.037	0.324
	y_{t+1}	−0.010	0.086	−0.003∗∗	−0.003	−0.050	0.600
	re_{t+1}	−5.380	27.695∗	−0.265	−0.076	0.105	0.179
	dy_{t+1}	−2.347	0.557	−0.015	0.848∗	0.736	0.000
	ρ	12.798∗	χ^2_3=2.621 (0.45)				

4.2. *Predictability*

In order to test the extent to which the model is consistent with the observed predictability of asset returns we analyze four implications of the model in Section 3. First we observe whether in those cases in which returns are predictable output is also predictable by the same variables. Second, we test whether in those cases in which returns are not predictable, output is not predictable either. Finally, we study if the restricted VAR model is consistent with the data and whether the estimate of ρ arising from the estimation of the restricted VAR model is reasonable in economic terms.

As far as the first implication of the model is concerned, we saw in Section 2 that returns are only clearly predictable by lagged returns, dividend yields, output and short-term interest rates in the US and the UK and for annual frequencies. Tables 3 and 4 confirm that result. Therefore, output can be predicted by the proposed set of variables in the US and the UK for both frequencies in agreement with the model.

The second implication we test is whether output is not predictable in those cases in which returns are not predictable. According to Tables 3 and 4 this implication fails in roughly half of the cases.

Finally, we check whether the restrictions on the VAR model implied by Eq. (7) are empirically plausible. According to the χ^2-test reported in Tables 3 and 4, the restrictions of the model are almost never rejected. A different picture emerges if one focuses on the estimated values of the inverse of the elasticity of intertemporal substitution (ρ). Notably, when we use quarterly data we only find significant estimates of this parameter for Italy. When we employ annual data, instead, the results are more promising and estimates of ρ are positive and significant for the US, France, Japan and Spain. We should bear in mind that, except in the case of US, the number of annual observations is relatively small.

Table 5
Volatility test. This table reports the values of ρ that satisfy the volatility restrictions of the model. The first column shows the minimum values of the parameter satisfying the volatility bound for a general output process. The second one presents the values of the parameter making volatility of model generated returns equal to the volatility of actual returns for the output process implicit in the VAR model

Country	Volatility Bound		VAR model	
	Quarterly	Annual	Quarterly	Annual
1. United States	1.94	1.78	4.78	4.86
2. United Kingdom	2.62	2.59	7.28	7.46
3. Canada	2.21	1.83	4.18	2.90
4. France	3.04	2.90	13.68	7.89
5. Germany	2.08	2.35	6.52	4.90
6. Italy	1.98	2.24	5.84	5.40
7. Japan	2.57	2.18	7.16	5.40
8. Spain	2.33	2.46	6.72	8.04

Overall, the evidence presented suggests that the model is not generally successful in explaining the conditional mean of stock returns in the countries considered. However, the model is able to provide, at least, an empirically plausible explanation in those cases in which the predictability of returns is more significant: the US and UK—for annual frequencies.

4.3. Volatility

In order to test whether the volatility of asset returns is consistent with that predicted by the model, we proceed as follows. First, we obtain the minimum values of the inverse of elasticity of intertemporal substitution that satisfy the general volatility bound of Eq. (18). Second, using the parameters of the VAR-model and Eqs. (6) and (19) we obtain the values of ρ that make volatility of the model-generated returns equal to the volatility of observed returns. For both exercises we use a value of δ equal to 0.95. Results are not sensitive to variations in δ within a plausible range. Table 5 reports the results of both volatility tests.

In the first exercise, we find that the volatility bound is satisfied in all cases and frequencies for values of ρ between 2 and 3. These results do not contradict the standard excess-volatility literature. Thus, Shiller (1981) and LeRoy and Porter (1981) derive volatility bounds which are only valid under constant discount factors (i.e. $\gamma = \rho = 0$). West (1988) using a model with time varying expected returns, determined by the consumption-based asset-pricing model, obtain a volatility bound which is only robust to values of the coefficient of relative risk aversion below one (i.e. $\gamma = \rho \leq 1$).[11] According to our results, it is not surprising that all three articles find evidence that implies rejection of the derived volatility conditions, since, within the consumption-based asset-pricing setup, a high value for ρ would be needed for the volatility bound to be sufficiently large. In fact, Grossman and Shiller (1981) were able to match actual and perfect foresight stock price volatilities,within the consumption-based asset-pricing model, for values of the coefficient of relative risk aversion above four (i.e. $\gamma = \rho > 4$).

Indeed, we have actually found, in our second exercise, that the parameter ρ (which would coincide with the relative risk aversion parameter in a standard consumption-based asset-pricing model) should be even larger, between 3 and 13, for the volatility of model-derived returns to be similar to that of observed returns. Although, the identification of a set of admissible values for the coefficient of relative risk aversion is difficult task, it seems hard to justify values as large as the ones required to satisfy the volatility conditions above. However, in our GIP framework, in which the coefficient of relative risk aversion (γ) is independent of the elasticity

[11] Campbell and Shiller (1989) using a linearized version of a model with time-varying expected returns to compute a variance ratio of the log dividend price ratio—allowing for the consumption-based asset-pricing model with constant relative risk aversion to compute expected returns—do not find statistically significant estimators of the coefficient of relative risk aversion parameter.

of intertemporal substitution $\left(\frac{1}{\rho}\right)$, the coefficient that governs the value of the model-derived volatility is unambiguously the inverse of the elasticity of intertemporal substitution. To the extent that, unlike in the case of risk aversion, a high aversion to intertemporal substitution of consumption is not necessarily unreasonable (see Weil, 1989), the generalization of preferences proposed by Epstein and Zin (1989) and Weil (1989) help explaining the so-called stock market volatility puzzle.

4.4. Joint test of predictability and volatility

The empirical exercises we have performed so far yield mixed results on the ability of a relatively standard equilibrium asset pricing model to explain the predictability and volatility of asset returns. In general the model has failed to explain satisfactorily the predictability of asset returns from that of real economic activity in most cases. However, the volatility of asset returns does not seem so big as to be explained by the fundamentals of asset prices. Moreover, using annual data for the US and UK, both the observed predictability and volatility of asset returns can be independently explained by the model for reasonable values of the preference parameters. A logical further step is to analyze the extent to which the model is able to simultaneously explain both features of the data for a single specification of preferences.

In this section we report the results of conducting a joint GMM estimation of the conditional mean and the unconditional variance of asset returns as a function of the model parameters μ and ρ. For the conditional mean we use Eq. (7) for which expected output is taken from the estimated VAR model. For the unconditional variance of returns we use Eq. (6) and the innovations of output obtained from the VAR model. We thus obtain three moment equations to estimate two parameters. The first two equations correspond to the standard OLS moment equations where the dependent variable is the observed returns and the regressors are a constant and the expected output. The third moment equation refers to the difference between the observed volatility of returns and the one predicted by the model according to Eq. (6). We then have one overidentifying restriction that will be used to test (through a χ^2 statistic) the ability of the model to match both the predictability and volatility of returns.

Results are reported in Table 6. Not surprisingly, the model fails to properly fit both moments of data when quarterly observations are used. Results are less negative when annual observations are employed. In this case, we find positive and significant estimates of the inverse of the elasticity of intertemporal substitution and values of the χ^2 tests that do not generally reject the null. It should be stressed, again, that results with annual data on countries other than the US should be viewed with great caution as they are obtained with few observations. Results on the US are probably more informative as they are obtained with much more degrees of freedom. In the US case, the overidentifying restrictions of the model are not rejected at a 1% significance interval, although more demanding criteria would imply a rejection of the null. The point estimate of ρ (4.1) is close to that required by the model to match

Table 6
Joint test of predictability and volatility. This table reports the values of μ and ρ that make the conditional expectation and volatility of the model generated returns equal to the conditional expectation and volatility of the actual returns. Standard errors in parentheses. Signif cance at the 5% level is denoted by $*$. The chi-square statistic tests the overidentifying restriction of the model

Country	Quarterly			Annual		
	μ	ρ	χ_1	μ	ρ	χ_1
1. United States	−0.043	5.188	40.175	−0.124	4.124	7.348
	(0.008)*	(0.346)*	(0.0000)	(0.041)*	(0.774)*	(0.010)
2. United Kingdom	−0.028	8.439	4.439	−0.097	6.608	2.564
	(0.011)*	(0.403)*	(0.035)	(0.073)	(2.229)*	(0.109)
3. Canada	−0.025	4.867	15.753	−0.037	2.922	5.306
	(0.009)*	(0.355)*	(0.0001)	(0.039)	(0.561)*	(0.021)
4. France	−0.051	14.416	9.881	−0.024	8.651	6.491
	(0.013)*	(1.385)*	(0.001)	(0.058)	(1.103)*	(0.011)
5. Germany	−0.002	5.786	14.174	0.026	4.179	5.707
	(0.011)	(0.727)*	(0.0001)	(0.052)	(1.294)*	(0.017)
6. Italy	−0.019	4.116	9.133	−0.132	3.980	4.578
	(0.014)	(0.933)*	(0.002)	(0.070)	(1.182)*	(0.032)
7. Japan	−0.024	6.148	15.170	−0.038	5.502	4.287
	(0.016)	(0.951)*	(0.0001)	(0.067)	(0.917)*	(0.038)
8. Spain	−0.038	7.109	25.931	−0.252	9.421	9.782
	(0.015)	(0.798)	(0.000)	(0.075)	(1.146)*	(0.001)

the volatility of returns, and slightly above the one which would match the conditional mean of returns.

On the whole, at least in the case of the US and for annual data, results are relatively supportive of the ability of the equilibrium model studied to replicate the observed predictability and volatility of asset returns.

Since we are using a linear approximation to equilibrium conditions, any rejection of the model could always be attributed to the higher order terms not considered in the empirical test. Nevertheless, this is unlikely as conditional higher order moments of output, which would form the higher order terms in a more accurate approximation, typically show low variability and covariability with the variables that help predicting returns.[12]

5. Conclusions

In this paper we have studied the ability of relatively standard equilibrium asset pricing models to explain two important empirical regularities of asset returns inten-

[12] As an example, with US annual (quarterly) data, the variability of the square of the conditional mean of returns is 45 (314) times lower than the variability of the conditional mean of returns.

sively documented in the literature: (i) returns can be predicted by a set of macroeconomic variables; and (ii) returns are very volatile. These empirical regularities are relevant because they have been often used to reject market efficiency.

We use the approximation technology for the solution of intertemporal asset pricing models recently developed by Campbell (1993) in the form suggested by Restoy and Weil (1998). Such approach permits asset returns to be explicitly expressed in terms of real economic variables. This makes it possible to test whether observed and model-generated moments of returns are sufficiently close, by using simple statistical procedures. The approximation technology shows how moments of aggregate returns, unlike those of excess returns, depend mainly on the elasticity of intertemporal substitution and not on agents' risk aversion. This is important, because we can analyze the extent to which the model fits the mean and variance of aggregate returns without considering any implication for the equity premium.

Using data form eight OECD economies (quarterly and annual observations) we have found that it is generally easier to explain the volatility of returns than their predictability. Thus, we have shown that for reasonable values of the elasticity of intertemporal substitution, the observed volatility of asset returns can be replicated by that of their real fundamentals according to standard intertemporal asset pricing models. This occurs for all eight countries using both quarterly and annual data.

It is much more difficult to justify the predictability of asset returns as an implication of equilibrium asset pricing models in most countries. The model is often unable to explain why returns are predictable in those cases in which they are and why they are not predictable in those cases in which they cannot be predicted by standard macro-variables.

Results are more positive for the model in the case of the US when annual data are used. In this case, the observed predictability and volatility of asset returns seems to be broadly compatible with the predictions of equilibrium models for a reasonable specification of preferences. This positive result, in the case of the US, as compared with those of other countries is not surprising. The assumptions of the model seem to fit better to relatively closed economies with large stock markets. In our sample, only the US economy is close to satisfying those assumptions. Moreover, it seems reasonable that equilibrium models behave better when applied to low-frequency data than when they are used to explain short-run movements, if one believes that possible deviations from fundamentals are somewhat transitory.

Appendix A

Consider that y_{t+1} follows a stationary ARIMA process

$$\Phi(L)\, y_{t+1} = \Theta(L)\varepsilon^{y}_{t+1},$$

where $\Phi(L)$ and $\Theta(L)$ are polynomials in the lag operator L and ε_{t+1} is a white-noise (serially uncorrelated and homoskedastic) process. If the process is stationary, the roots of the polynomial $\Phi(L)$ must lie outside the unit circle. The same condition on $\Theta(L)$ guarantees that the moving average is invertible, so that it can be expressed in autoregressive form. For example, if we assume that y_{t+1} follows an MA(1) process with parameter θ, then,

$$y_{t+1} = (1-\theta L)\varepsilon^{y}_{t+1},$$

and also,

$$\begin{aligned}(E_{t+1} - E_t)y_{t+j+1} &= \varepsilon^{y}_{t+1} && \text{if } j = 0\\ &= -\theta\varepsilon^{y}_{t+1} && \text{if } j = 1\\ &= 0 && \text{if } j > 1\end{aligned}$$

Then, from Eq. (6) in the text,

$$r_{t+1} = \mu + \rho y_{t+1} + (1-\rho)(1-\delta\theta)\varepsilon^{y}_{t+1}.$$

It is straightforward to extend this calculation to any moving average process, including the infinite order case. This is of particular importance since, by the Wold theorem, it can be used to represent a general stationary time series.

Hence, if the production process is

$$y_{t+1} = \varepsilon^{y}_{t+1} + \sum_{k=1}^{\infty}\theta_k\varepsilon^{y}_{t+1-k},$$

Eq. (6) can be written as

$$r_{t+1} = \mu + \rho y_{t+1} + (1-\rho)(1 + \delta\theta_1 + \delta^2\theta_2 + ...)\varepsilon^{y}_{t+1}.$$

This formula gives us a simple rule for evaluating returns from the moving average representation of the output process: simply discount the moving average parameters, and add them up.

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